NEW SIGNAL PROCESSING SCHEME FOR THE ANALYSIS OF ELECTROMAGNETIC IMAGES

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INTRODUCTION

Electromagnetic methods of nondestructive testing find widespread application in industry. A vast majority of the defect characterization schemes using electromagnetic methods involve estimation of the size and/or shape of the defect on the basis of a one dimensional signal obtained by scanning the surface of the test specimen using a suitable transducer [1-3]. Recent years have witnessed increasing interest in the development of imaging techniques for characterizing defects. As an example, eddy current imaging methods involve a raster scan of the surface of the test specimen to obtain a two dimensional image whose elements represent the real or imaginary components or alternatively the magnitude or phase of the impedance of the eddy current probe [4,5]. In the case of magnetostatic imaging methods, the specimen under test is scanned by a flux sensitive transducer such as a Hall probe. The image is obtained, typically, by treating the value of either the normal or tangential component of the flux density at each sample point as a gray level [6]. Inverse techniques proposed to date rely largely on phenomenological models for analyzing the images to obtain estimates of the size and shape of the defect [7-10]. Unfortunately, these techniques call for considerable computing resources. This paper presents a novel defect characterization scheme involving singular value decomposition of electromagnetic images.

The approach described in this paper involves two steps. The first step involves compression of the data contained in the image as shown in Fig. 1. The compressed data set is then treated as a feature vector and during the second stage, conventional pattern recognition techniques are used for classification. Mapping the signal on to a smaller dimensional feature space not only reduces the computational effort involved but also the performance of the classification procedure. The philosophy is somewhat similar to the Fourier descriptor approach proposed by Udpa and Lord [11] for the classification of differential eddy current impedance plane trajectories, in that the signal is mapped to a smaller dimensional feature space prior to classification. The mapping procedure, both in the case of the Fourier descriptor method as well as the approach described in this paper, allows resynthesis of the original signal/image from the mapped parameters. The following section presents a brief description of the singular value decomposition technique which is used for compressing the information contained in the image.

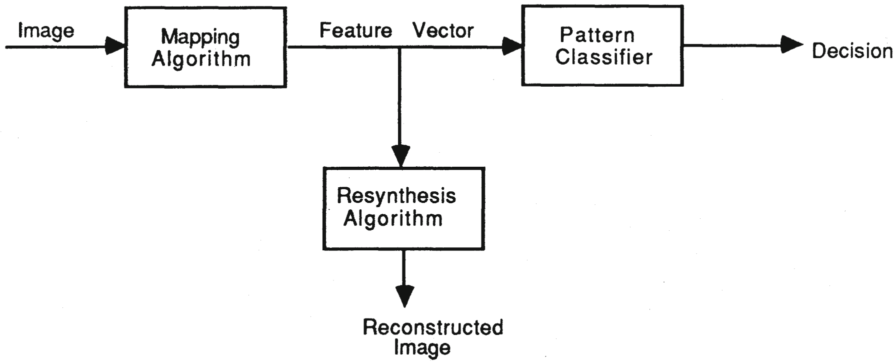


Fig. 1. Block Diagram of the Defect Characterization Scheme.

SINGULAR VALUE DECOMPOSITION

The singular value decomposition (SVD) technique has been used extensively in such areas as numerical analysis and image processing [12-15]. It is based on the simple premise that for any complex (mxn) matrix A of rank r, there exists matrices U, V and Σ such that

$$A = U \Sigma V^T \tag{1}$$

where U and V are unitary matrices of dimensions (mxn) and (nxn) respectively and $\Sigma = \text{diag}(\sigma_1, \sigma_2 \ldots \sigma_r, 0, \ldots 0)$ with

$$\sigma_1 \geq \sigma_2 \geq \sigma_3 \; - - \geq \sigma_r$$

The columns of U and V are called the left and right singular vectors of A while $(\sigma_1, \sigma_2 \ldots \sigma_r)$ are called the singular values of A. The singular values are equal to the positive square roots of the eigen values of $A^H A$, where A^H is the conjugate transpose of A. Space limitations preclude a detailed review of the properties of the SVD and interested readers are referred to references 12 and 13 for a discussion on the subject. However, the property of interest for the problem on hand lies in the fact that the singular values $\sigma_1, \sigma_2 \ldots \sigma_r$ as given by the diagonal elements of Σ are in decreasing order and are equal to zero when $k > r$. Thus the SVD can be used as a tool for estimating the rank of a matrix. In addition by rewriting equation (1) in the form

$$A = \sum_{k=1}^{r} \sigma_k U_k V_k^T \tag{2}$$

where U_k and V_k represents the kth column of U and V respectively, we observe that the original image can be synthesized from the left and right singular vectors of A and the corresponding singular value. Equation (2) can also be approximated by

$$A \simeq \sum_{k=1}^{m} \sigma_k U_k V_k^T \tag{3}$$

where $m \leq r$. Equation (3) can be interpreted as a sum of eigen images, each of which is the outer product of the left and right singular vector weighted by the corresponding singular value. Figure 2b through 2f show resynthesized versions of an image shown in Fig. 2a for various values of M. It is clear that as M approaches r the synthesized image looks very similar to the original image. It is clear that the degree of compression obtained is closely linked to the rank r of the image matrix in relation to its size (mxn) as well as to the desired quality of the resynthesized image. Low values of M lead to a high degree of compression but result in poor resynthesized images and vice-versa. Electromagnetic images tend to be smooth in nature (i.e. neighboring columns and rows tend to be similar) and consequently the rank of the image is usually very low. Considerable amount of compression can, therefore, be achieved by using this method.

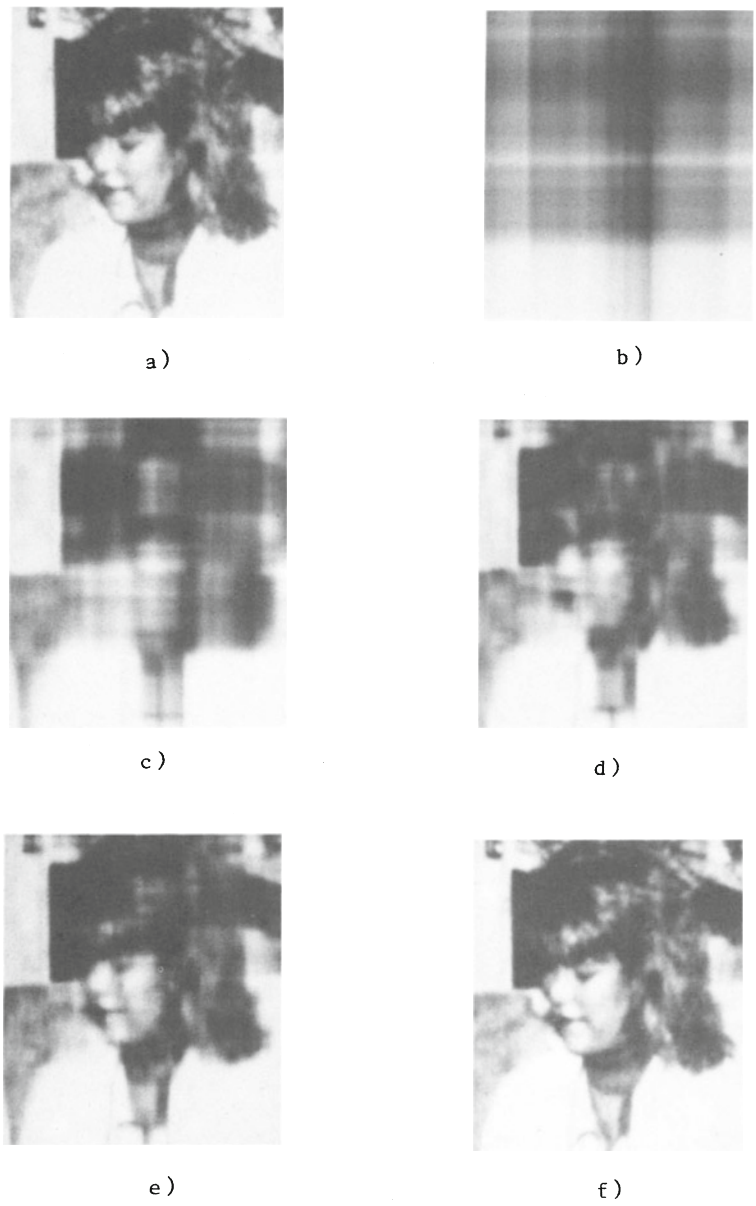


Fig. 2. Original (a) and Resynthesized Images (b-f) Obtained With M = 1, 2, 4, 8 and 12.

Several methods for computing the SVD have been proposed [13,16]. The authors have used LINPACK [17] which has implemented one of the more robust algorithms for computing the SVD.

CLASSIFICATION

Once the left and right eigen vectors and the singular values are computed, we choose M of each and incorporate them into a feature vector. One of several pattern classification algorithms such as the nearest neighbor or clustering algorithms [18] can be used for classifying the feature vector in the feature space.

EXPERIMENTAL TESTS AND RESULTS

In order to confirm the feasibility of the approach, defects as shown in Fig. 3 were machined. The system shown in Fig. 4 was used to scan the test specimen using an absolute eddy current probe operating at 10 KHz. The data representing the real and imaginary components of the eddy current probe was transferred to a VAX 11/780 computer for further analysis. The eddy current instrument was adjusted to obtain maximum sensitivity along the imaginary axis. Consequently only the imaginary component images were used for analysis. In order to minimize the effect of variations in gain of the eddy current instrument, all the images were normalized prior to analysis. Fig. 5 shows some of the images obtained. Fig. 6 and 7 show resynthesized versions of two of the defect images for various values of m in equation (3). It is clear that the rank of the images is very low and substantial levels of data compression can be achieved. Since the number of defect types is very small the feature vector was synthesized using the first four eigen values only. If a larger defect prototype set is used, the left and right singular vector may have to be incorporated into the feature vector to obtain better discrimination. Feature vectors for each of the four defects were obtained and used as prototypes. The feature vector for the fifth defect was computed and classified using the minimum distance rule [18]. The fifth defect was correctly classified as belonging to the same class as the first defect. Although the authors recognize that the defect set is very small, the potential of the method as a tool for the classification of defects has been clearly established.

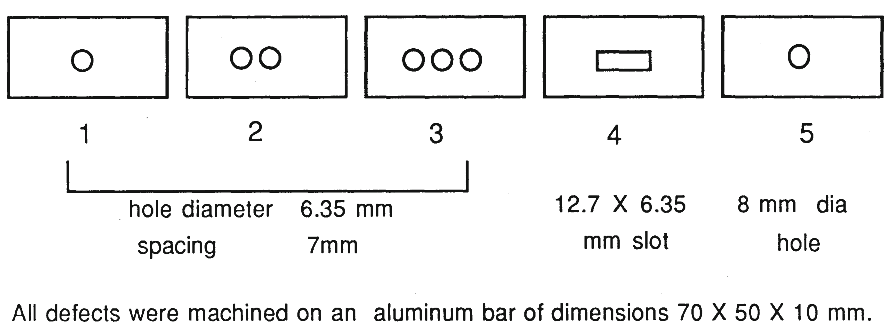


Fig. 3. Defect Set Used for Assessing the Feasibility of the Method.

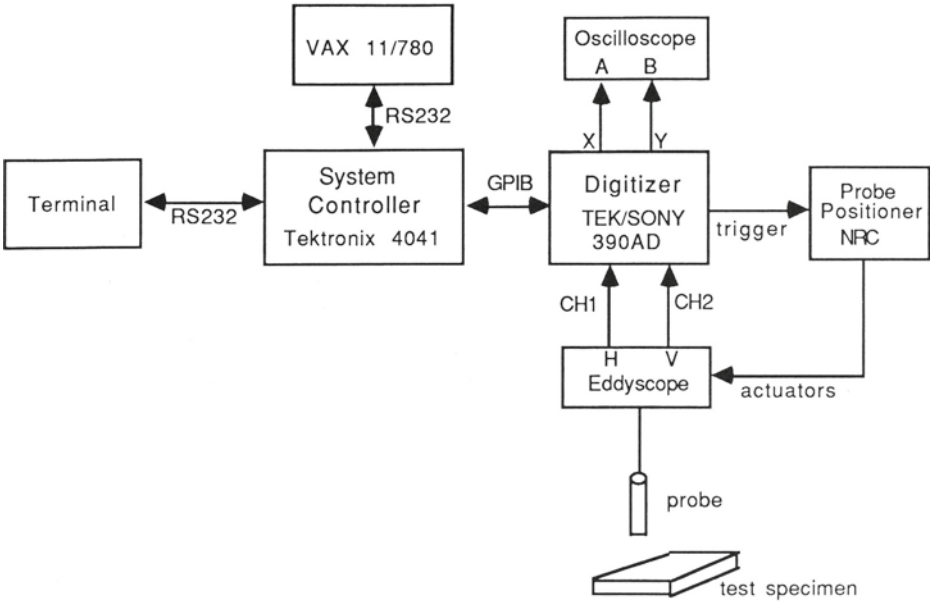


Fig. 4. Experimental Set-up Used for Obtaining Eddy Current Images.

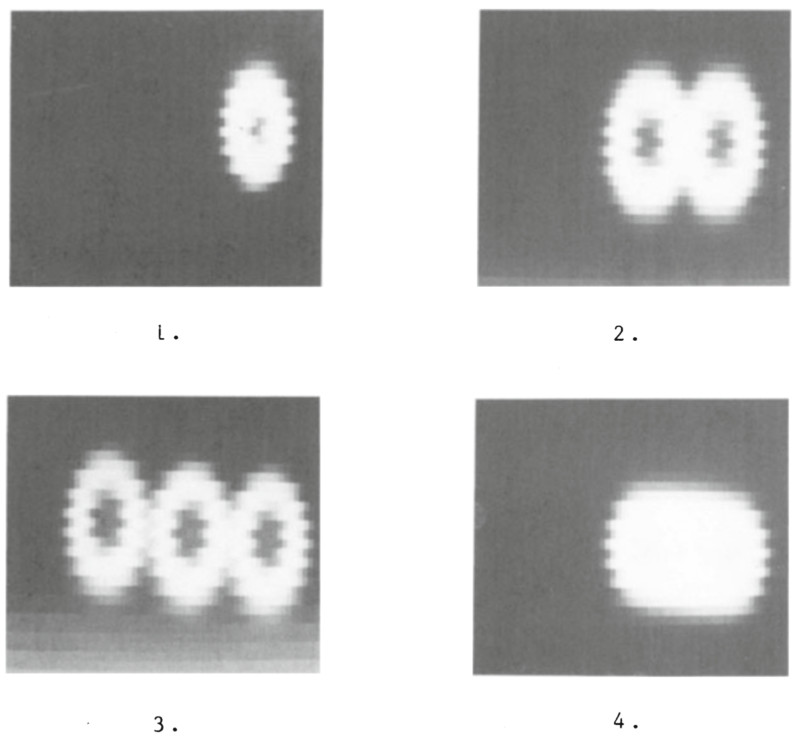
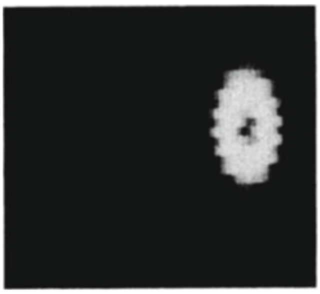
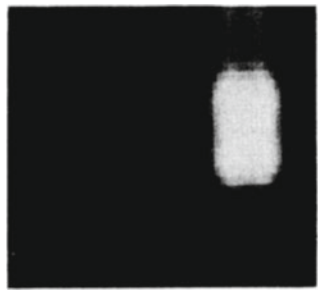


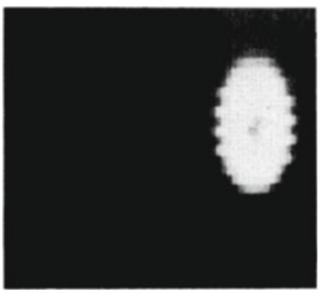
Fig. 5. Eddy Current Images Obtained Using the Defect Set Shown in Figure 3.



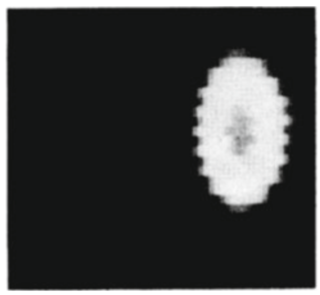
a)



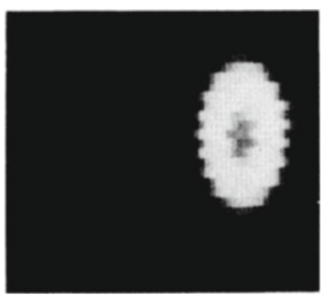
b)



c)



d)



e)

Fig. 6. Original (a) and Resynthesized Images (b-e) Obtained with M = 1, 2, 3 and 4.

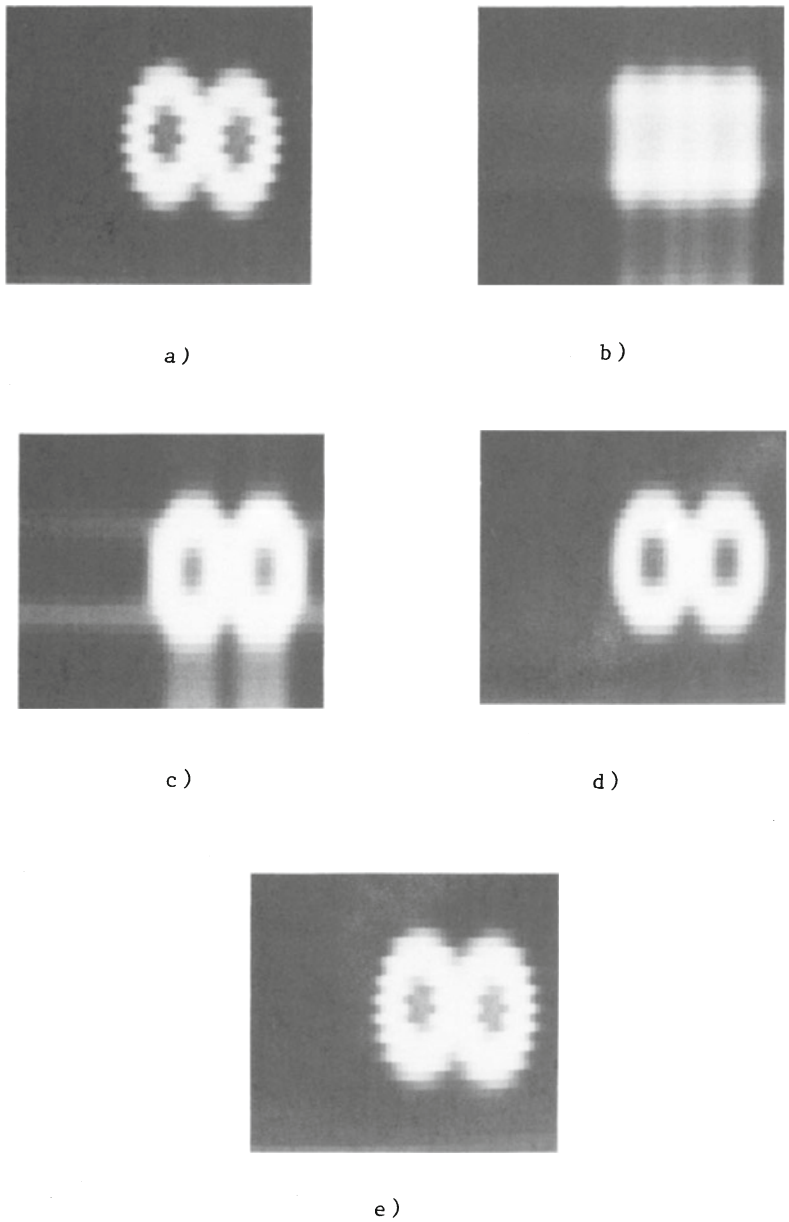


Fig. 7. Original (a) and Resynthesized Images (b-e) Obtained with M = 1, 2, 3 and 4.

CONCLUSIONS

A novel method for analyzing electromagnetic images has been presented. Although results confirming the validity of the approach for analyzing only eddy current images was presented, the method can be used for characterizing magnetostatic as well as ultrasonic images with equal ease.

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